Supplementary Online Content

Morgan DJ, Bame B, Zimand P, et al. Assessment of machine learning vs standard prediction rules for predicting hospital readmissions. *JAMA Netw Open*. 2019;2(3):e190348. doi:10.1001/jamanetworkopen.2019.0348

eAppendix. Baltimore Score Machine Learning Model Development

eTable. Categories of Features in the Final Machine Learning Model

This supplementary material has been provided by the authors to give readers additional information about their work.

eAppendix. Baltimore Score Machine Learning Model Development

The same process was followed over three hospitals using each hospital's individual databases from data collected from September 1, 2014 through August 31, 2016.

The B-score, presented as a rank with a range of 0-1, was produced by a predictive model trained using machine learning techniques and algorithms. The outcome to which this model was trained was all-cause readmissions within 30 days of the index visit, excluding planned readmissions, based on CMS definitions. The model was "bespoke", meaning it was trained specifically to fit data from these hospitals in order to produce more accurate predictions for the relevant patient and provider populations. Even though this model is not, and was not meant to be, a general-purpose tool, the same techniques used to create this model could be used to produce a custom model for any hospital where similar data is available.

To create this predictive model, a wide range of data was extracted from each of the three hospital's Epic-based electronic health record. This data was then cleaned, mapped, and "engineered" to produce features suited to machine learning tasks. Initially almost 9,000 features were produced. Many different model types were trained, optimized, and evaluated using this set of features. During this process the feature set itself was culled using model-specific methods. Each model and subset of features was evaluated using AUROC across several data sets using a K-fold cross-validation strategy to minimize over-fitting and maximize generality.

Best results were obtained with a weighted combination of 500+ Gradient Boosted Regression Trees (GBRT) and a Convolutional Neural Network (CNN), with the final feature set culled to 382 features. The final set of features included several representing facility and department to reflect differences between hospitals.

eTable. Categories of Features in the Final Machine Learning Model

Feature Category Description

Admission Type Inpatient, Outpatient, Emergency, Elective, Direct, etc.

Admitting Diagnosis ICD Code

Admitting Service Hospital Service at admission (post-ER)

Admitting Source Home, Physician Referral, ER, Skilled Nursing Facility,

Assisted Living, etc.

Affiliated with a Specific

Church Yes/No

APR DRG Mortality Code Numeric: 1-5 for this visit, and delta from prior visit max APR DRG Severity Code Numeric: 1-5 for this visit, and delta from prior visit max

Basic Measures Age (at admission), gender, height, weight, and weight change

over time

BMI, BSA, and %IBW Calculated from height and weight, and change from prior

visits

Blood Number of units and types of units infused

Breathing Assistance Yes/No and Type, this visit and prior visit: Nasal cannula, Face

mask, Tracheostomy, BiPap (not ventilator)

Central Line Categorized by line type, this visit and prior visits
Characterization of Home Several variables extracted from 2010 Census and

Address subsequent ACS data (U.S. Census Bureau)

Charlson Comorbidity Index
Diagnostic History

Charlson Comorbidity Index
ICD Codes from prior visits

Discharge Disposition Home, Skilled Nursing Facility, Assisted Living, Acute Care

Facility, Hospice, AMA, etc. Hospital Service at discharge

Discharge Service Hospital Service at discharge
Discharge Status Hospital Service at discharge
Alone, Accompanied, Ambulance, Stretcher, etc.

Distance from UMMS

Distances between geo-coded latitudes/longitudes and facility

facilities latitudes/longitudes

Employer Self, County, State, Military, BWMC, Large local employer

(Giant Foods, Walmart, BGE, etc.)

Employment Status Employed/Unemployed this visit, Employed/Unemployed prior

visit

English Fluency Yes/No

ER Frequency 4 Values: 3 Months, 6 Months, 12 Months, 24 Months

Ethnic Group Standard list

Identifies as Having a

Religion Yes/No

Substance Abuse Illegal and legal, as a series of binary indicators Inpatient Days 4 Values: 3 Months, 6 Months, 12 Months, 24 Months

Intubated Yes/No for this visit, Yes/No for prior visit

Lab Meta Number of lab orders, number of unique lab tests, etc.

Lab Tests Min, Max, Mean, and Latest (Na, K, blood counts, hemoglobin,

etc.), not limited to this visit

LDA Lines, drains, and airways (categorized and counted), not

including central lines

Legal Substance Abuse Yes/No current (including Tobacco, Alcohol, etc.), Yes/No

historical

Length of Stay In hours, calculated as date/time of discharge minus date/time

of admission

Marital Status Married, Single, Divorced, Widowed, Separated, Partnered

Total and categorized (counts by pharmacy class and Medications

therapeutic class) this visit and prior visits

Alone/Accompanied, Ambulance, Car, On Foot, Law Mode of Arrival

Enforcement, etc.

Outpatient Visits Attended/Skipped

Pain Score

Post-Discharge Coded

Diagnoses

Primary Insurance Classification

Procedure History

Procedures

Radiology Meta

Residence Change

Staff Alerts

Mental Health

Ventilator Visit History

Vital Signs

WDL

4 Values: 3 Months, 6 Months, 12 Months, 24 Months Min, Max, Mean, and Most recent (not limited to this visit) ICD Codes (looking for CKD, COPD, CHF, AKI, Diabetes,

Chronic Pain. Mood Disorders. etc.)

Self Pay, Medicare, HMO, Military, Commercial, Carefirst/Blue

Cross. etc.

Number and types of surgical procedures performed prior to

this visit

Number and types of surgical procedures performed this visit Number of radiology orders, number of unique radiology study

types, etc.

Within the past 2 years represented as two values: Yes/No,

and how recent (number of months)

VRE, MRSA, VOR, etc.

Categorized "affect", suicide risk, etc.

Yes/No this visit and prior visits along with total vent days Running monthly totals of counts and types of visits within the

past 2 years

Features generated by auto-encoders (HR, Resp, BP, Temp,

SaO2, etc.), not limited to this visit

Physical Exam "within defined limits" Most recent HEENT

WDL, Cardiovascular WDL, Respiratory WDL, etc.